Numerical Simulation of a Battery Thermal Management System Under Uncertainty for a Racing Electric Car

crédit : Jaguar MENA

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La simulation pour la mobilité électrique, NAFEMS

November 13, 2019

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Battery Thermal Management for Electric Vehicles

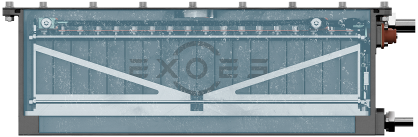
E-racing Car requirements

- Several charge/discharge cycles in small time intervals
- High Power from the Electrical Engine and Fast recharging : increased heat loads on Battery Pack

Battery Thermal Management for Electric Vehicles

Immersion Cooling System by EXOES

- Electric Cells immersed in dielectric cooling fluid.
- Heat exchanged directly from cells to the fluid.
- Good thermal homogeneity within the Battery Pack.



Multi-Fidelity Simulation and Uncertainty Quantification

Main PhD project overview (2018-2021)

- Numerical Simulation of Battery Thermal Management Systems (BTM) :
  - High-Fidelity Model (HF) : based on Computational Fluid Dynamics (CFD)
  - Low-Fidelity Model (LF) : "0D Model" based on energy balance equations
- Uncertainty Quantification Methods to take into account uncertainties related to BTM Systems.
- Multi-Fidelity numerical tool : coupling LF and HF models
  - Reduce computational costs
  - Perform UQ methods including High-Fidelity simulations

Multi-Fidelity Simulation and Uncertainty Quantification

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  - Reduce of computational costs
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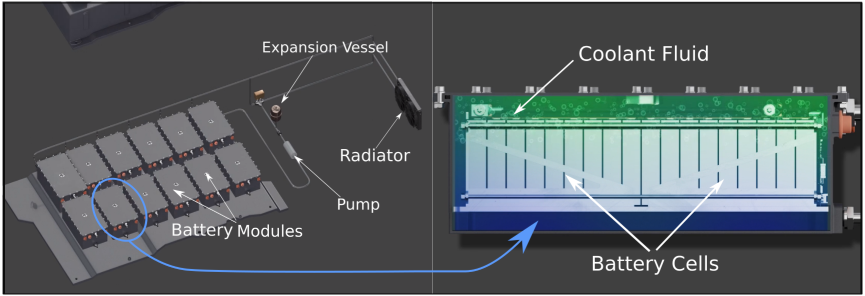
Today's focus :
Performances Analysis of the LF Model with Uncertainty Quantification methods.

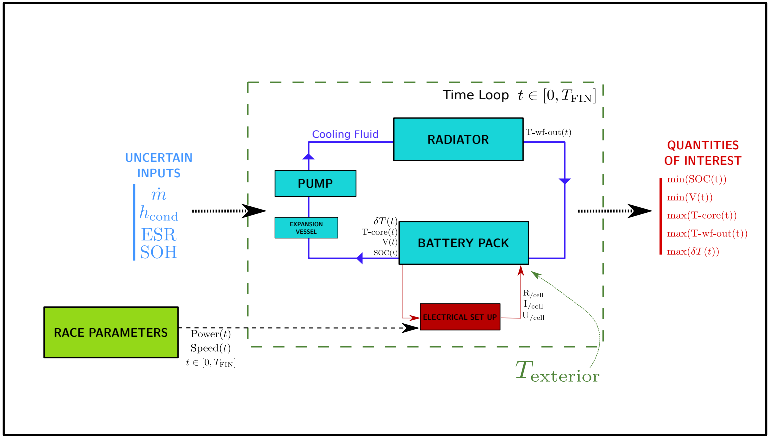
The Exoes Battery Thermal Management System (BTMS)

Cooling Circuit

Battery Module



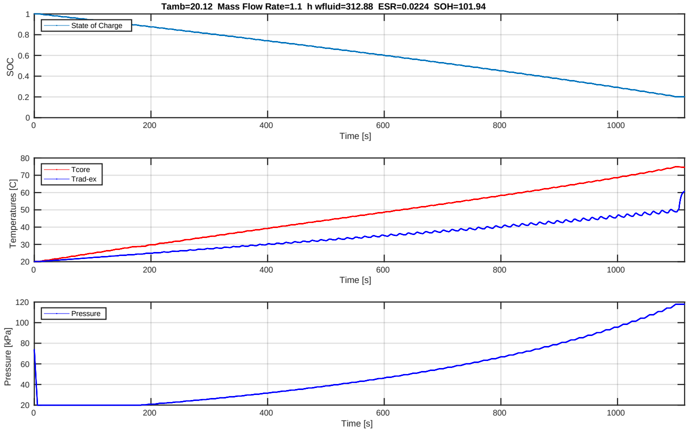
The Low-Fidelity Model



Case Study : Race

- Race duration : 20 minutes
- Maximal Power required by the electrical engine : 180 kW
- More than 70 accelerations and braking sequences.

What the LF model computes



Take Uncertainties Into Account

Choice of **4 uncertain parameters** : lack of knowledge to set an exact value.

x_1	Massic Flow Rate	$\dot{m}$	$[1.08; 1.3]$	$\mathrm{kg.s^{-1}}$
x_2	Heat Transfer Coefficient	h_{cond}	$[250; 360]$	$\mathrm{W.m^{-2}.K^{-1}}$
x_3	Equivalent Serie Resistance	ESR	$[0.01; 0.025]$	Ω
x_4	State Of Health	SOH	$[98; 102]$	%

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Goals of Uncertainty Propagation :

Estimate the variability of the QOI with respect to the input parameters uncertainties.
(Statistical moments, Quantiles, Sensitivity analysis, ...)

Uncertainty Characterization

STEP 1 : Sampling of the 4 uncertain inputs. N_S sample points following uniform distribution.

x_1	Massic Flow Rate	$\dot{m}$	$[1.08; 1.3]$	$\mathrm{kg.s^{-1}}$
x_2	Heat Transfer Coefficient	h_{cond}	$[250; 360]$	$\mathrm{W.m^{-2}.K^{-1}}$
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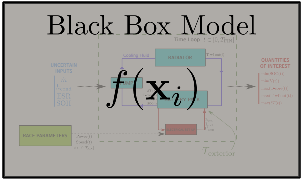
Uncertainty Propagation

STEP 2 : Perform N_S simulations with the Numerical Model, seen as a Black Box

Uncertain Inputs — **Quantity Of Interest**

$$\mathbf{x}_i = \begin{pmatrix} \dot{m}_i \\ h_{\mathrm{cond}_i} \\ \mathrm{ESR}_i \\ \mathrm{SOH}_i \end{pmatrix} \longrightarrow$$



$$\longrightarrow Y_i = f(\mathbf{x}_i)$$

$$i = 1, \dots, N_S$$

Uncertainty Propagation

STEP 3 : Compute the variability of the QOI with respect to the input uncertainties of the system

Uncertainty Propagation

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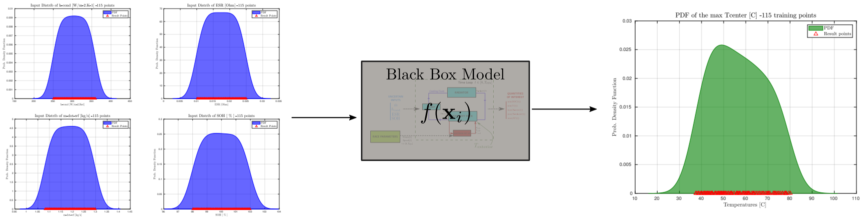
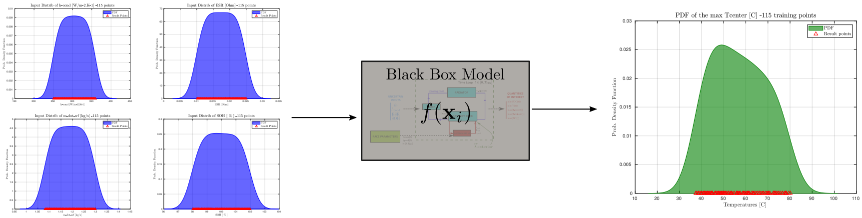
Distribution of the QOI $\max_{t \in [0, T_{\text{FIN}}]} (T_{\text{center}}(t))$, with 115 sampled points



Uncertainty Propagation

STEP 3 : Compute the variability of the QOI with respect to the input uncertainties of the system

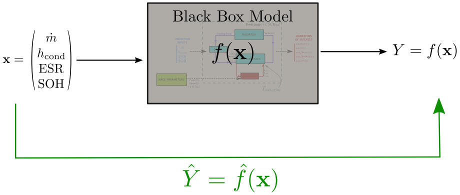
Distribution of the QOI $\max_{t\in[0,T_{\mathrm{FIN}}]} \left(T_{\mathrm{center}}(t)\right)$, with 115 sampled points



But 115 points is not enough to get accurate distribution.
Monte Carlo method too expensive with computational model $f(\mathbf{x})$.
Need to replace $f(\mathbf{x})$ by a fast-to-compute surrogate model

Kriging Surrogate Model

Need to replace $f(\mathbf{x})$ by a fast-to-compute surrogate model



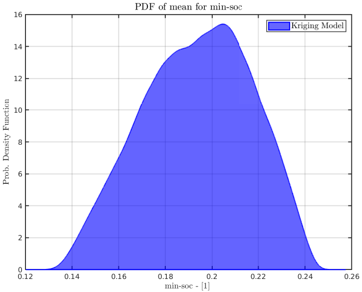
Kriging Based Surrogate Model

Based on Gaussian Process Regression

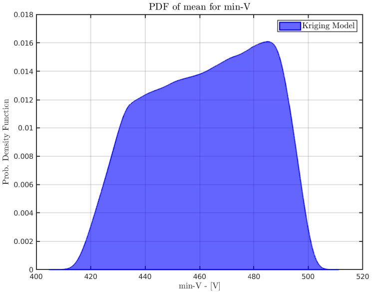
Compute an estimation $\hat{Y} = \hat{f}(\mathrm{x})$ of the QOI, built on the 115 training samples from the numerical model $f(\mathrm{x})$

Distributions of the QOI

Computation of the PDF for each QOI at $T_{\mathrm{amb}} = 15^{o}C$
estimated with surrogate model



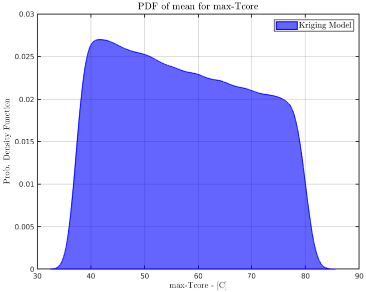
$$\min_{t\in[0,T_{\mathrm{FIN}}]}(\mathrm{SOC}(t))$$
$$\mathrm{COV} = 11.99\%$$



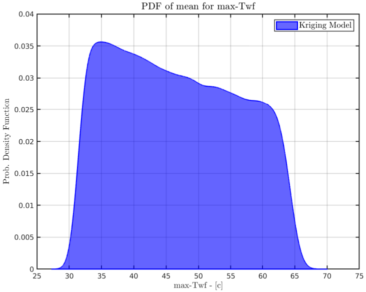
$$\min_{t\in[0,T_{\mathrm{FIN}}]}(\mathrm{V}(t))$$
$$\mathrm{COV} = 4.54\%$$

Distributions of the QOI

Computation of the PDF for each QOI at $T_{\text{amb}} = 15^o C$
estimated with surrogate model



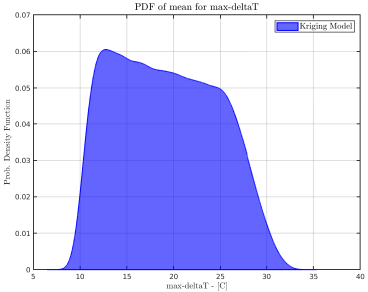
$$\max_{t\in[0,T_{\text{FIN}}]} (T_{\text{center}}(t))$$
$$\text{COV} = 21.49\%$$



$$\max_{t\in[0,T_{\text{FIN}}]} (T_{\text{wf-out}}(t))$$
$$\text{COV} = 20.21\%$$

Distributions of the QOI

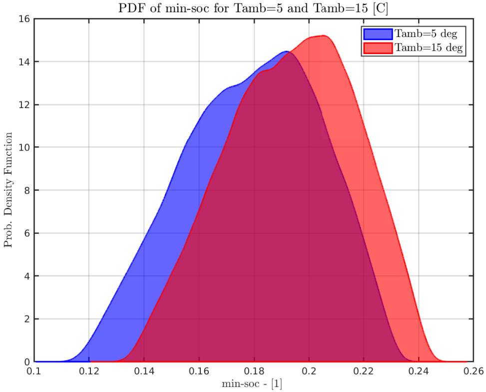
Computation of the PDF for each QOI at $T_{\text{amb}} = 15^o C$
estimated with surrogate model



$$\max_{t \in [0, T_{\text{FIN}}]} (\delta T(t))$$
$$\text{COV} = 28.37\%$$

Results for 2 different T_{exterior} scenarios

Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^o C$ and $T_{\text{exterior}} = 15^o C$



$$\min_{t \in [0, T_{\text{FIN}}]} (\text{SOC}(t))$$

Results for 2 different T_{exterior} scenarios

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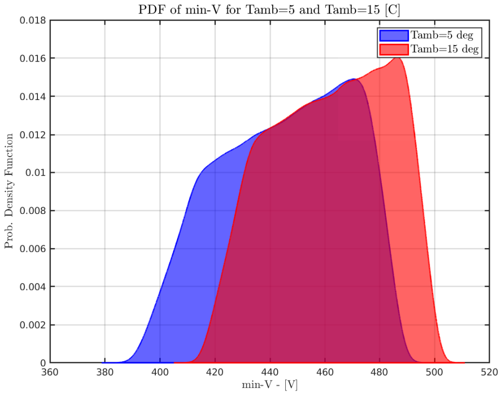

$$\min_{t \in [0, T_{\text{FIN}}]} (\mathrm{V}(t))$$

Results for 2 different T_{exterior} scenarios

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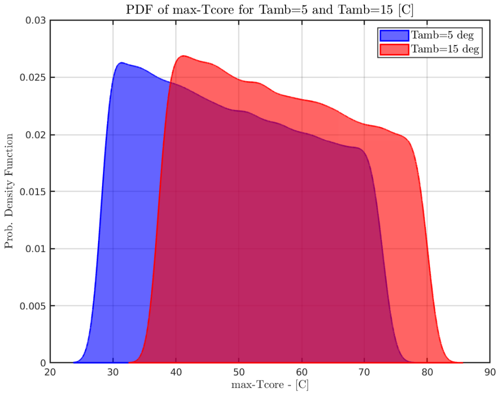

$$\max_{t \in [0, T_{\text{FIN}}]} (T_{\text{center}}(t))$$

Results for 2 different T_{exterior} scenarios

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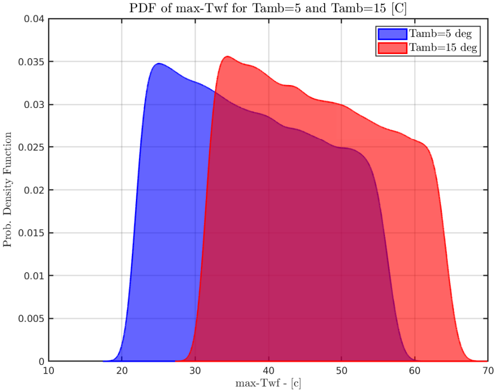
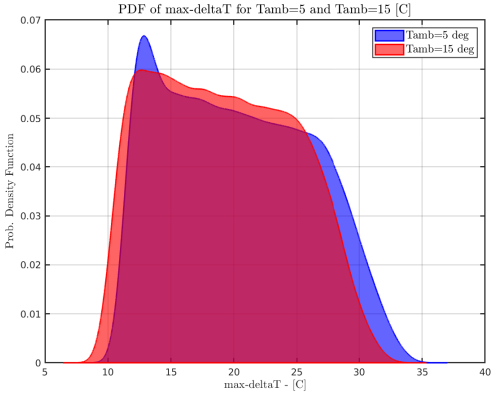


$$\max_{t \in [0, T_{\text{FIN}}]} (T_{\text{wf-out}}(t))$$

Results for 2 different T_{exterior} scenarios

Comparison of the variability of some QOI for $T_{\text{exterior}} = 5^o C$ and $T_{\text{exterior}} = 15^o C$



$$\max_{t \in [0, T_{\text{FIN}}]} (\delta T(t))$$

Sensitivity Analysis Study

Goal of Sensitivity Analysis :

Show which uncertain input parameter has the most influence on the variability of our quantity of interest.

$\rightarrow$ Gain more knowledge about the behavior of a complex model.

Sensitivity Analysis Study

Show which uncertain input parameter has the most influence on the variability of our quantity of interest.

Mathematical Framework : ANOVA Decomposition

Analysis Of Variance

Input $\mathbf{x} = (x_1, x_2, x_3, x_4)$

Black-box numerical model f seen as :

$$f(\mathbf{x}) = \underbrace{f_0}_{mean} + \underbrace{\sum_{i=1}^{4} f_i(x_i)}_{first\ \ order} + \underbrace{\sum_{i_1=1}^{4} \sum_{i_2=i_1+1}^{4} f_{i_1 i_2}(x_{i_1}, x_{i_2})}_{second\ \ order} + \cdots + \underbrace{f_{1,\ldots,4}(x_1, \ldots, x_4)}_{fourth\ \ order}$$

Sobol Index for a QOI : $Y_{\mathrm{QOI}} = f(\mathbf{x})$

Sensitivity Analysis Study

Show which uncertain input parameter has the most influence on the variability of our quantity of interest.

Mathematical Framework : ANOVA Decomposition

Sobol Index for a QOI : $Y_{\text{QOI}} = f(\mathbf{x})$

First Order Sobol Index for input $\mathbf{x}_i$:

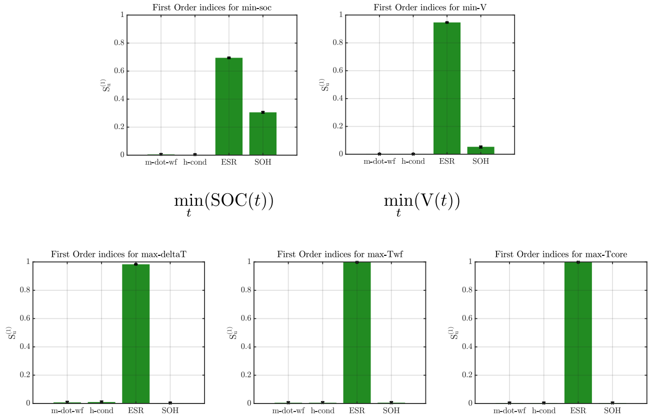
$$S_i = \frac{\text{Var}(\mathbb{E}[Y_{\text{QOI}}|\mathbf{x}_i])}{\text{Var}(Y_{\text{QOI}})}$$

$\text{Var}(\mathbb{E}[Y_{\text{QOI}}|\mathbf{x}_i])$ = variance of the mean value QOI "knowing" the input $\mathbf{x}_i$

$\text{Var}(Y_{\text{QOI}})$ = main variance of the QOI

S_i quantifies the main effect of x_i on the contribution to the variance of Y_{QOI}

First Order Sobol Indices Results



$\min_t(\mathrm{SOC}(t))$ $\min_t(\mathrm{V}(t))$

$\max_t(\delta T_{\text{cell}}(t))$ $\max_t(T_{\text{wf-out}}(t))$ $\max_t(T_{\text{center}}(t))$

First Order Sobol Indices for each QOI (case $T_{\text{exterior}} = 15\ ^oC$)

What we learned from UQ Analysis

- Set up of a Low-Fidelity Model : gives an insight of the system behaviour with low computational costs
- Predicting the behaviour of the system while taking into account uncertainties on the physical input parameters
- Sensitivity Analysis gave robust estimation of the impact of some parameters on the Quantities Of Interest
  - ESR is the most determinant parameter for all QOI related to the temperature of the cells or the cooling fluid
  - SOH must not be neglected for minimal voltage of the cell

Perspectives

- From the results of Sensitivity Analysis : reduce the number of inputs, set-up simpler models
  - example : for $\max(T_{\text{center}}(t))$, get direct relationship between this QOI and ESR parameter

- Set up a High-Fidelity Model : based on CFD (Navier-Stokes + Energy Conservation 3D equations). Improve current simulations (influence of the geometry, find local heat spots on battery cells etc...).

- Represent the same physical case with HF model and LF model to perform multi-fidelity simulation of BTM Systems

Thank you for listening

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